

MAPPING LAND COVER TYPES FROM VERY HIGH SPATIAL RESOLUTION IMAGERY: AUTOMATIC APPLICATION OF AN OBJECT BASED CLASSIFICATION SCHEME

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ABSTRACT:

Although geographic object based image analysis (GEOBIA) has been successfully applied to derive local maps (1-10s km²) from very high spatial resolution (VHR) image data (pixels < 1.0 x 1.0 m), its potential for automatically mapping large areas remains unknown. The aim of this study was to create and apply a GEOBIA method to automatically map land cover classes in subsets with different environmental and land cover characteristics from VHR image data. Airborne Vexcel Ultracam-D image data with four multi-spectral bands and 0.25 m pixels were captured for the study area, located 50 km from Melbourne, Victoria, Australia. Five subsets showing different environments and characteristics were selected for the study. Four of them were used to create a GEOBIA classification method for mapping land cover types. A step-wise approach was adopted, where individual steps of segmentation and classification were used to establish a contextual knowledge base. Thus, context features became useful for classifying land cover types. The following land cover types were mapped from the five subsets: woody vegetation, non-woody vegetation; water bodies, bare ground, urban features and agricultural areas. The overall accuracy of the four land cover maps used to develop the GEOBIA classification scheme was 77.5%. The classification accuracy was calculated using 100 validation sites per land cover class, visually identified from the Ultracam-D data. Finally, the effectiveness of replicating the GEOBIA classification scheme was tested against the independent fifth subset. This classification produced very similar results, with an overall accuracy of 74.8%, which indicates that the developed GEOBIA classification scheme may be automatically applied to other independent areas, and potentially for larger spatial extent mapping.

1. INTRODUCTION

Knowledge of the spatial distribution of land cover types is essential for many purposes. Land cover maps are frequently used as a tool for urban planning and natural resource management, and they can assist in targeting and prioritizing risk mitigation activities (Cleve et al., 2008).

Remotely sensed image data are a very valuable source of information for land cover mapping which have been extensively used for this purpose (Foody, 2002; Lucas et al., 2007). In the recent years, a significant research effort has been placed on the analysis of very high spatial resolution (VHR) imagery, mainly due to the increased availability of VHR sensors (Johansen et al., 2008).

A Geographic Object-Based Image Analysis (GEOBIA) was used for this study. GEOBIA has been successfully adopted for the analysis of VHR imagery in a broad range of scientific disciplines. Encouraging results have been obtained, for example, for mapping urban areas (Chen et al., 2009), land cover types (Antonarakis et al., 2008), forest fuels (Giakoumakis et al., 2002; Arroyo et al., 2006), terrestrial oil spills (Hese & Schmullius, 2009), as well as in change detection analyses (Johansen et al., 2010) and the assessment of the riparian zone condition (Johansen et al., 2007).

Although there are a number of studies that confirm the benefits of the GEOBIA of VHR imagery, they are restricted to small study areas; of 1 to 10 Km². Very little is known about how these methods would behave for larger areas, showing variation in environmental and land cover characteristics.

The aim of this study is to develop and apply a GEOBIA method to automatically map land cover classes in areas with different environmental and land cover characteristics from VHR image data. Four subsets of Ultracam-D image data with four multi-spectral bands and 0.25 m pixels were used to develop a GEOBIA method for mapping land cover classes using the Definiens Enterprise Image Intelligence Suite. The effectiveness of replicating the GEOBIA method was tested against an independent fifth subset of the same image data set.

2. DATA AND METHODOLOGY

2.1 Study Areas

Five independent study areas were selected for this project (Figure 1). They were located near Bacchus Marsh, 50 km to the northwest of Melbourne, Victoria, Australia. The terrain around Bacchus Marsh comprises a wide range of landscape features, including agricultural crops and orchards, reservoirs, urban settlements, deep gorges and forested areas. Several rivers and creeks can be found throughout this area. Because

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the aim of this research was to develop and apply a transferable processing routine using GEOBIA to automatically extract land cover classes, the high diversity of landscape features and land cover classes of this region made it suitable for this study.

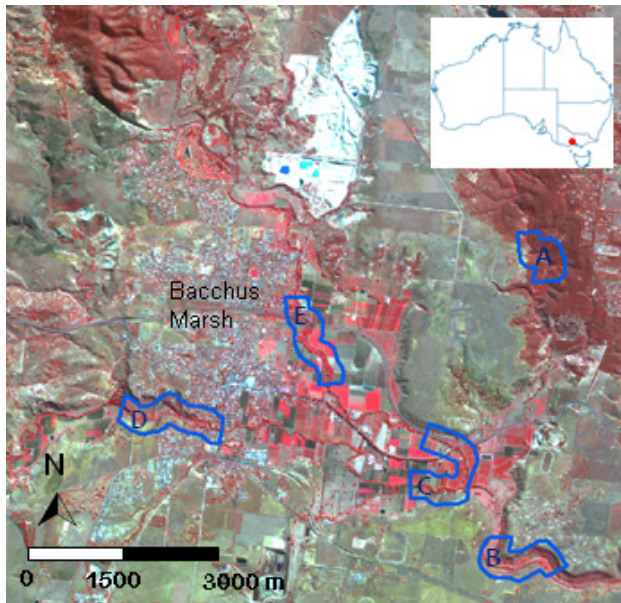


Figure 1: Location of the study area, located around the Victorian town of Bacchus Marsh (Australia). The extent of the five selected subsets (A to E) is shown on top of a SPOT-5 image of the area.

2.2 Data Acquisition and Pre-Processing

Airborne Vexcel Ultracam-D image data were captured on the 19, 20 and 23 of April 2008 with a spatial resolution of 0.25 m pixels consisting of four multi-spectral bands located in the blue, green, red and near infra-red (NIR) part of the spectrum. The image data were captured at approximately 3000 m height with side and forward overlaps of 30% and 70% respectively. A total of 448 frames (7500 x 11500 pixels per frame) were captured at 16 bit. These data were orthorectified by the data provider prior to delivery. The image data were not atmospherically corrected as suitable meteorological information was not available.

In order to assist the land cover type identification, two more bands were calculated from the multi-spectral data and incorporated to the analysis. The Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988) was calculated to assist discrimination of the vegetation. From the four multi-spectral bands the first principal component (PC1) was produced and used as an indicator of general brightness.

Five subsets were selected in order to maximise the variability of land cover classes within the region. The first subset (A) was representative of the steep forested hills of the north-eastern part of the study area. Subset B was selected to represent a reservoir and flat areas located at the bottom of the reservoir. Subset C was representative of agricultural crops and orchards. Subset D reflected an area of urban settlements. Subset E was used for the validation of the GEOBIA routine and it included all the land cover classes that were found in the

previous subsets. The area of these subsets ranged from 0.6 to 1 km².

2.3 Geographic Object-Based Image Analysis

Five independent projects, one per subset, were generated using the Definiens Enterprise Image Intelligence Suite for batch-processing. Each project contained all the bands derived from the Ultracam-D data (blue, green, red, NIR, SAVI and PC1). A digital elevation model (DEM) with 20 m pixels and a thematic layer representing the centreline of the main rivers and creeks were also included in the GEOBIA. The DEM was provided by the Department of Sustainability and Environment, Victoria Government. The stream centreline layer was produced from manual delineation of aerial photography.

A GEOBIA segmentation and land cover classification routine was developed and applied using subsets A-D. A sequential multi-resolution segmentation was carried out in order to avoid exceeding the maximum allowable number of objects. Each subset was first divided into tiles, which were individually segmented, and then stitched back together for further analysis (Johansen et al., 2008). The blue, green, red, NIR, SAVI and PC1 bands were used for the multi-resolution segmentation. The composition of the homogeneity criterion was focused on the spectral information (weight of 0.9) and to a limited extent on shape (weight of 0.1), with similar importance given to all the image bands.

Land cover class descriptions were based on a combination of spectral values and class-related context features. Spectral values were mainly used in the form of ratios to avoid unique thresholding of individual spectral bands. The majority of employed processes in the developed rule set focused on the shape of the objects (e.g., size, asymmetry), their context (e.g. distance to streambeds), and texture (e.g., variability of spectral values within an object).

A step-wise approach was adopted for the GEOBIA segmentation and classification routine, where individual classification processes were used to develop an expert knowledge base. Through the analysis, context features gradually became more powerful, allowing discrimination of less obvious land cover elements.

2.4 Accuracy Assessment

The validation of the land cover classifications was based on visual identification of a stratified random selection of 50 validation sites from the Ultracam-D data and 50 validation sites from the classifications for each land cover class. Each validation site was a circumference of 1 m diameter. A combined error matrix was produced for subsets A to D. The user's, producer's and overall accuracies and the kappa statistic were also calculated.

The accuracy assessment of the land cover map of subset E was carried out independently using the same approach as for the previous subsets (A to D). This allowed an independent evaluation of the transferability of the GEOBIA routine.

3. RESULTS

Study areas A to D were used for developing a GEOBIA classification scheme to map land cover types from the 0.25 m

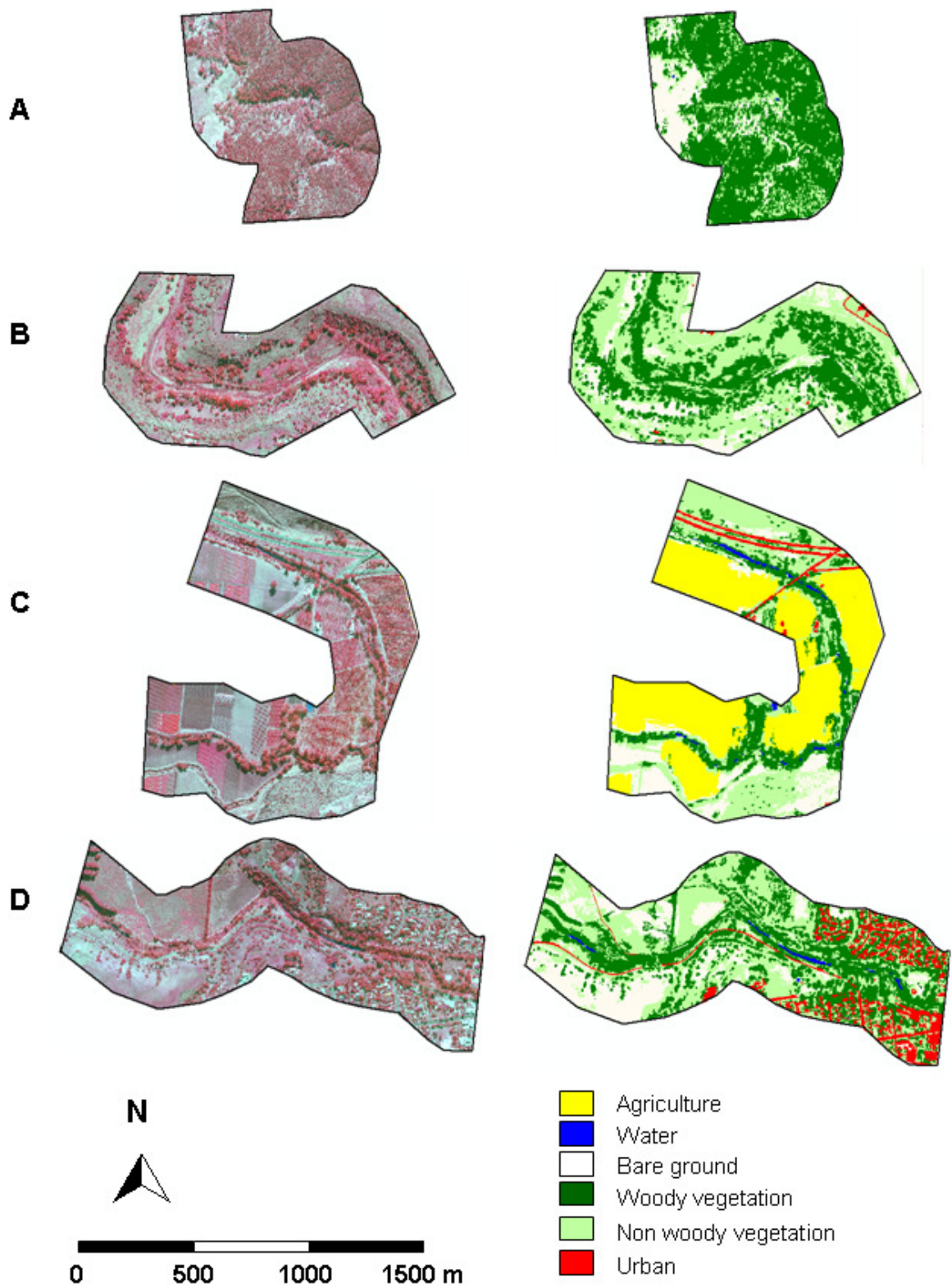


Figure 2: Green, red and NIR colour composites of the Ultracam-D image data for subsets A to D (left) and their respective land cover maps (right).

resolution Ultracam-D image data. The land cover maps obtained for subsets A to D are shown in Figure 2, and their corresponding error matrices are presented in Table 1. Urban elements showed the highest producer's and user's accuracies of 98.6 and 95.9%, respectively, followed by agriculture (87.2 and 92.1%) and water bodies (84% and 100%). The main source of error was misclassification of non-woody vegetation being incorrectly classified as bare ground and woody vegetation. These classes showed a gradual change from bare ground, to non-woody vegetation, to woody vegetation, and the boundaries represented by thresholds between them were difficult to establish, even visually. The continued overall accuracy for the four subsets was 77.5%, with a Kappa statistic of 0.73.

Table 1: Error matrix, of the land cover type classifications derived for subsets A to D. (Agr = Agriculture; BG = Bare ground; NWV = Non Woody Vegetation; Urb = Urban; Wt = Water; WV = Woody Vegetation; Prod. Acc = Producer's accuracy in %; U.Ac. = User's accuracy in %)

	Agr	BG	NWV	Urb	Wt	WV	Total	U. Ac.
Agr	1149	76	8	14	0	0	1247	92,1
BG	52	647	122	0	0	0	821	78,8
NWV	38	548	644	0	156	23	1409	45,7
Urb	0	55	0	1300	0	0	1355	95,9
Wt	0	0	0	0	1101	0	1101	100
WV	79	2	552	4	55	1305	1997	65,3
Total	1318	1328	1326	1318	1312	1328	7930	
Prod. Acc.	87,2	48,7	48,6	98,6	83,9	98,3		

The potential of the developed GEOBIA method to be applied to independent subsets was evaluated by implementing it on subset E, which consisted of all six land cover classes (Figure 3). A visual inspection of the result revealed a good performance of the designed GEOBIA method. The segmentation approach was found reliable, providing meaningful image objects, and the step-wise classification approach proved to be efficient for classifying land cover classes in the independent subset.

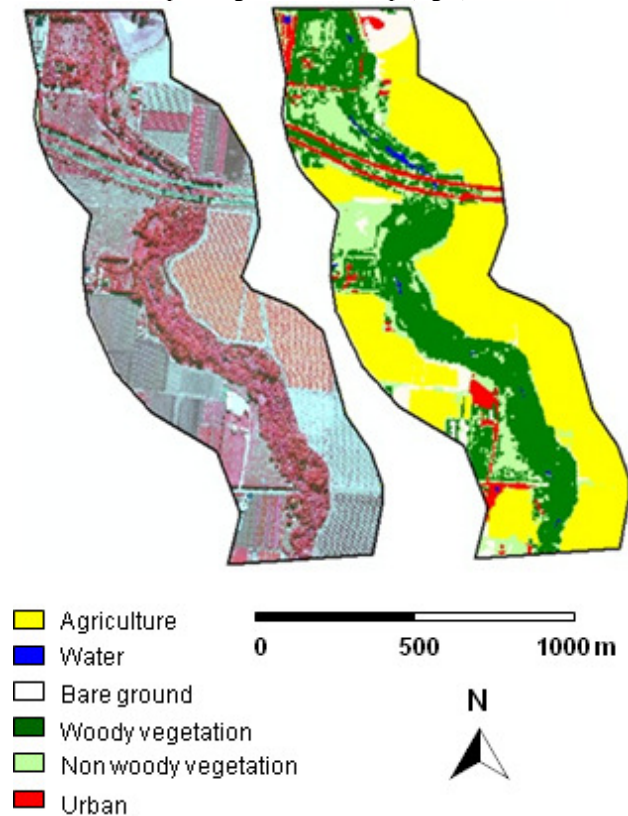
Table 2: Error matrix of the land cover type classification derived for subset E. (Agr = Agriculture; BG = Bare ground; NWV = Non Woody Vegetation; Urb = Urban; Wt = Water; WV = Woody Vegetation; Prod. Acc = Producer's accuracy in %; U.Ac. = User's accuracy in %)

	Agr	BG	NWV	Urb	Wt	WV	Total	U. Ac.
Agr	579	25	0	0	0	0	604	95,9
BG	38	38	0	0	0	0	76	50,0
NWV	38	108	50	0	42	0	238	21,0
Urb	0	55	0	511	0	0	566	90,3
Wt	0	0	0	0	275	0	275	100
WV	47	0	188	4	27	240	506	47,4
Total	702	226	238	515	344	240	2265	
Prod. Acc.	82,5	16,8	21,0	99,2	79,9	100		

The error matrix of this classification showed trends similar to those of subsets A to D, with slightly accuracies (Table 2).

Urban elements showed very high levels of producer's and user's accuracies of 99.2 and 90.3%, respectively. Agricultural fields had producer's and user's accuracies of 82.5 and 95.9% and water bodies were mapped with 79.9 and 100% producer's and user's accuracies. For subset E, the percentage error caused by misclassification of non-woody vegetation as woody vegetation and bare ground as non-woody vegetation was larger than that for subsets A to D, yielding producer's and user's accuracies of 21%. The overall accuracy for the land cover classification of subset E was 74.8%, with a Kappa statistic of 0.69.

Figure 3: Green, red and NIR colour composites of the Ultracam-D image data for subset E (left) and the corresponding land cover map (right).



4. DISCUSSION AND CONCLUSIONS

Although visually very powerful, the small pixel size of the VHR Ultracam-D image data makes land cover mapping challenging. Reflectance characteristics of individual land cover classes show significant variation, and spectral properties are less suitable for land cover identification. This constraint becomes especially limiting when the study area becomes larger, since the range of observed environments increases. In this study, we have developed a classification scheme that could be accurately applied to map land cover types from VHR Ultracam-D image data over a variety of environments.

The development and application of a contextual knowledge base within the GEOBIA allowed us to formulate precise land cover class descriptions, leading to an accurate and transferable classification scheme. In contrast with traditional pixel-based analysis, the highest accuracies were found for the urban and agriculture land cover types. In that sense, the incorporation of context information to the analysis was of significant help in

order to identify land cover types from VHR image data over a variety of environments.

Further research is encouraged in order to test the systematic application of GEOBIA classification schemes for VHR image data over large study areas (100's of km²), where computing capacities might become a limiting factor.

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